DEVELOPMENT OF EFFECTIVE HIGH PERFORMING DEEP LEARNING BASED MODELS FOR BREAST CANCER PREDICTION

A SYNOPSIS

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M. SARATHKUMAR

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(DEEMED TO BE UNIVERSITY)

ANANDNAGAR, KRISHNANKOIL – 626126

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1. INTRODUCTION

An early type cancer discovered in world is breast cancer, which is categorised by the development of abnormal cells in the body. Statistical data from American Cancer Society from 2017, shows that breast cancer is the second prominent cause of mortality among women. Consequently, it is important to find breast cancer cells early as possible, so as to reduce the death rate. Therefore, imaging tests and breast biopsies are used to detect breast cancer, however imaging tests are more conservative and the biopsy is seen as an invasive approach. Hence, Magnetic resonance imaging (MRI), mammography as well as ultrasound, are few of the methods that are employed to classify breast cancer. The main screening technique for early breast cancer diagnosis is mammography, which has been proved to be the most reliable method. Like other medical treatments, mammography is not perfect despite being extremely precise. A novel breast cancer detection system with an improved architecture that combines breast mammography pictures with Convolution Neural Network (CNN) is generated to address the aforementioned short comings.

The mutual features of medical images like unidentified noise, poor image contrast, inhomogeneity, flimsy borders and disconnected areas, which have an effect on the content of medical photographs. Pre-processing, segmentation, feature extraction as well as classification are the four distinctive stages of this technology, which significantly overthrow the foretasted problems. In order to get accurate results, each of these phases thoroughly analyses the input image that contains cancer. In the pre-processing stage, undesirable interruptions in the input image are eliminated and image features are improved. When denoising an image for the first time, linear filters are used, but their capacity is insufficient since they obscure the contra stand edge region of the image. This specific limitation is greatly reduced by the application of Mean filters. As a result, the mean filter is used instead of the median filter to mitigate the aforementioned issues. The mean filter has the ability to maintain edge information within an image while preventing calculation errors by statistically processing the relationship between picture pixels. The median filter has a number of significant drawbacks, including being relatively costly and difficult to calculate. Henceforth, in this research, by implemented pre- processing process, the denoising image is effective and also mitigate the above mentioned concerns.

After that noise-free image is divided into various segments by using a variety of methods. Since the K-means technique has many positive attributes, including maximum effectiveness, accuracy, simplicity, which is preferred to address the issues in the image segmentation process. However, the usage of this filter is limited by its lower discriminative capacity. To acquire more accurate findings, it is recommended to segment the image by adopting Fuzzy C-Means (FCM) method. Never the less, this technique has flaws like sensitivity to initial settings and being stuck in local optima. Hence, Independent Component Analysis (ICA) is developed, which is one of the key methodologies to address all those difficulties. Because it specializes at quickly and effectively collecting the optimum independent image features from the collection of vectors. Still, these methods might not be the ideal choice in some circumstances for particular applications due to their high computing costs. Thus, the developed work introduced the Deep CNN and VGG-16 topology, which dramatically extracts the image features.

For the most precise stage finding of breast cancer, classification is carried out after feature extraction. Metaheuristic algorithm are implemented for the classification process, PSO is one of the metaheuristic algorithm which directly seeks out the optimal solution within the problem space. But, the iterative procedure has a low convergence rate in high-dimensional space, making it easy to enter a local optimum. Consequently, GA has been demonstrated to be a potent search technique that solves the aforementioned issues. At the same time, finding the best or most effective combination of the secriteria can be challenging and problematic. So that the proposed work, implemented CNN-Bi-LSTM-GRU-AM (CBGAT) approach to precisely classify the occurrence of breast cancer.

2. LITEARTURE SURVEY

Many systems employed to predict breast cancer and a thorough investigation of breast cancer detection is presented below. In general, a strategy based on image processing and the approaches involved are briefly examined. Furthermore, the approaches for segmentation, classification, feature extraction, and optimization are discussed. The surveys that correlate to the various methodologies, which have been generated in recent years with their advantages and disadvantages, are described below.

Abhijith Reddy Beeravolu *et al,* [1] have proposed efficient image pre-processing techniques to provide databases that can reduce the computing time required by neural networks and increase accuracy and classifications rates. This method is used to the computational efficient image pre-processing techniques for eliminating as much unnecessary area from mammographic images as feasible. Though, to improve efficiency, the validation data required to be employed to tune the parameters and make adjustments to networks are necessary.

Esther Jebarani et al, [2] have presented an adaptive median filter which is employed for noise reduction, edge preservation, image quality development, and smoothness in pre-processing procedure. The proposed method is important for differentiating between tumors that are both benign and malignant. As a result, a cutting-edge method has been used to precisely detect tumor locations. The recommended approach has been used to locate the tumor and visually identify tumors. Although, no reliable methods have yet been produced.

Aber Saber *et al,* [3] have proposed an innovative deep learning (DL) method to effectively aid an automatic identification and diagnosis. This method Minimize the training time by removing only the problematic are as from breast images. Modifying the already trained network classifier is used to improve the effectiveness of classification. However, tuning as well as freezing methods need to improve dataset's mass lesion categorization precision.

Vivek Patel *et al,* [4] have presented an adaptive regularized deep learning network (GARL-Net) for exact precise breast cancer categorization. There al enhanced function of loss is graph based adapted standardized complements crossing entropy loss. But this method need to be used for more than just classification and it also has the potential to enhance the neural networks' capacity to learn for use in image processing.

David Murcia-Gómez *et al,* [5] have presented various pre-processing techniques and DL models for a collection of photos of breast cancer. To carry out a comparable statistical study and look at a larger range of designs to find the models that perform well. Because it takes a lot of time and resources to perform numerous simulations for each possible combination of filters and DL models this flaw is caused by the high computational cost.

Haeyun Lee *et al,* [6] have proposed a channel attentive ness modules with multi scale grid average pooling for an exact segmentation of breast cancer areas in ultrasound images. The proposed modules with multi scale grid pooling of averages is not only useful for ultrasonic segmentation of images. Never the less, due to their poor performance, recently proposed approaches like FCN and U-Net still require improvement to give better semantic segmentation for detecting breast cancer using ultra sound imaging.

Dilovan Asaad Zebari *et al,* [7] have demonstrated an effective model on an innovative thres holding method as well as machine learning system. The developed trainable segmentation technique produced the most accurate segmentation. The development and use of a completely automatic segmentation method recognize breast region as well as remove the muscles of the pectorals from mammograms images. ROI occasionally has no border or a border that is incredibly hazy. However, the proposed model cannot be used to obtain the missing border.

Abdel hameed Ibrahim et al, [8] have presented a technique based on the Chaotic Swarm Algorithm (CSSA) for breast cancer utilizing thermal images. The proposed techniques segment images of various healthy and unwell cases with more robustness. Though, to assess the proposed algorithms, which is more challenging in medical and non-medical issues and that need to be examined.

Jie Xing *et al,* [9] have developed a novel DL technique for segmenting lesions in 2D ultrasound images termed SPCGAN (Semi pixel wise Cycle Generative Adversarial Net). The technique uses a generative adversarial net as well as Fully CN to segment a lesion based on prior information. The accuracy of segmentation is still very high. However, it is crucial to concentrate on creating reliable algorithms on various ultrasonic image types to make computer techniques useful in practical applications.

Epimack Michael *et al,* [10] have introduced region based segmentation, which is often utilized for conventional procedures, with region growing techniques. Additionally, a median filter is a powerful device for eliminating noise. Nevertheless, breast tumors are complicated, and experts in artificial intelligence do not comprehend the requirements for therapeutic use.

Sourav Pramanik *et al,* [11] have provided a novel integrated framework for the segments of the breast region that proposes three different approaches for locating breast boundary's various sections. This technique can be utilized to completely automate any thermo gram based breast anomaly detection approach by taking the place of the manual segmentation stage. But, the proposed approach does not separate the breast region in circumstances where thermo grams do not contain sufficiently or execute to asymmetrically.

Xiaofeng Qi *et al,* [12] have proposed a segmentation approach for breast cancer CTV during CT planning that is based on deep neural networks. A new dynamically strung convolution technique that outperforms traditional convolution has been developed to allow networks to focus on breast mass in slices. Yet, it is challenging to identify which portion of the complete slice has the appropriate breast and which portion needs to be excised.

Rui Man *et al,* [13] have implemented a unique approach for classifying breast cancer termed as Dense Net 121 – Ano GAN. When a patch based classification method as well as enhance classification performance of proposed approach effectively tackle the issue of incorrectly labeled patches. Nonetheless datasets generated from whole slide images (WSIs) contain numerous incorrectly labeled patches, making the adoption of a patches based classification algorithm particularly difficult.

Mohammad M. Ghiasi *et al,* [14] have introduced a classification system for cancers of the breast that makes use of the Wisconsin Breast Cancer Database (WBCD), ML as well as data mining methods. Additionally, majority of the tools that are available have excessive complexity, poor organization, and over fitting. However, it is anticipated that the random forests and Extra tree algorithms need to play a significant role in healthcare and medical systems for screening and diagnostics.

Selina Sharmin *et al,* [15] have provided a hybrid, reliable methodology for detecting breast cancer that combines the strength of DL with ensemble based ML techniques. The system can learn as well as detect hidden patterns from complicated breast cancer images to the combination of DL, and ML algorithms add interpretability and generalisation skills. To improve breast cancer detection and

effects of diagnosis, amount of areas need to be researched in the future.

Zexian Huang *et al,* [16] have created a model called the Hierarchical Clustering Random Forest (HCRF). This method is employed to conduct a clustering study on decision trees by comparing similarities between all of the decision trees. Selecting representative trees from various groups allows for construction of a hierarchical clustering random forest with small similarity and great accurateness. However, to display and to consider structural diversity in upcoming investigation, it is essential to diversify the decision trees in the random forest.

Ali M. Hasan *et al,* [17] have provided a completely automated as well as effective deep to pographies extraction approach makes use of the spatial data. The proposed framework showed extremely desirable characteristics for classifying breast cancer from breast MRI scans. Never the less future research need to involve the application of rigorous authentication of removed deep learning characteristics to identify non-mass lesions as opposed to mass lesions, which are more likely to be detected.

Nikhil anand Arya *et al,* [18] have developed a stacked based ensembles ML model for estimating life expectancy of breast cancer patients with the aid of CNN and RF. Genetic expression, variations in copy number, and medical information are some of the multi-modal inputs used in this model. This design may potentially be utilized for other conditions with a multimodal input requirement. Even though proposed method has outperformed every other prediction model currently in use, but it is still need to validate it using other breast cancer data sets.

Ehtisham Khan Jadoon *et al,* [19] have introduced a network model based on heterogeneity deep learning for precise multimodal data based breast cancer predictions. The development of heterogeneous stacking based models for predicting breast cancer is the main aim. The shortcomings of the breast cancer prognostic models frequently rely on a single modality as well as might not deliver precise forecasts for patient survival.

3. PROBLEM STATEMENT

Breast cancer is one of the greatest diverse and deadly illnesses in today's world, affecting the lives of many women. Several techniques are used for detecting

precise prediction of breast cancer. The conventional approach implement the efficient image pre - processing techniques to provide databases that reduce the computing time required by neural networks and increase accuracy and classifications rates. But, the validation data needs to be employed to tune the parameters and make adjustments to networks are necessary. Therefore, the stacked based ensembles ML model for estimating life expectancy of breast cancer patients with the aid of CNN and RF is employed. Nevertheless, it still need to validate it using other breast cancer data sets. Hence, a network model based on heterogeneity deep learning for precise multimodal data based breast cancer predictions is utilized to overthrow the issues mentioned above. But, this method frequently rely on a single modality and might not deliver precise forecasts for patient survival. As a consequence, this research proposed a feature extraction technique with the novel classification topology for overcome the aforesaid problems.

4. OBJECTIVES

In this research work, an ovel optimized CNN technique for breast cancer classification is implemented to overthrow the abovementioned issues and the contribution of the relevant research work is illustrated below as follows,

- To enhance colour contrast as well as to remove noises from the input breast image by adopting pre-processing technique.
- To extract all required features from the Pre –processing data with the aid of Deep CNN and VGG-16 feature extraction topology.
- To early diagnosis of breast cancer patients by adopting CBGAT classification approach for prediction.

5. PROPOSED METHODOLOGY

The proposed research work to classify breast cancer is implemented in three stages and are stated as follows.

- Implementation of breast cancer classification using Artificial Bee Colony optimized CNN.
- Implementation of Moth flame Optimized CNN for enhancing breast cancer detection.
- Implementation of CNN-Bi-LSTM-GRU-AM topology for efficient breast cancer prediction.

5.1 Implementation of breast cancer classification using Artificial Bee Colony optimized CNN

To precisely classify the existence of breast cancer, this approach uses a special ABC optimised CNN. The input management is given to the pre-processing stage, which filter the noise from the input image with the aid of Wiener filter. Then the noise free output is deliver to Segmentation for detecting the region affected and to choose the important segments of the images, which is actively segment by utilizing Fuzzy C-means approach. Moreover, the segmented output from the FCM technique is given to the feature extraction for extracting all required features with the aid of GLCM approach. The output from feature extraction is classified by implementing CNN technique. For predicting accurate classification, the developed method utilized the ABC optimization topology for CNN. Nevertheless, better accuracy, sensitivity and specificity is needed. Thus, a moth flame optimized CNN is implemented for improving breast cancer detection.

5.2 Implementation of Moth flame Optimized CNN for enhancing breast cancer detection.

For improving breast cancer prediction, the Moth flame optimized CNN is implemented in this developed work. Initially, the input image has low quality with noise, which require suitable pre-processing technique for further process. Therefore, the Adaptive Median filter is implemented for removing noises from the input image without losing the sharpness of the edges. The noiseless output from the pre - processing stage is given to the Segmentation process, which selects the required image instead of processing the entire image by adopting U-Net algorithm. Furthermore, the selected image is deliver to the Feature extraction for choosing relevant data from the segmented image with the aid of GLCM approach. The CNN technique is implemented to classify the output images from feature selection. For attaining accurate classification, the Moth Fly optimized CNN is developed in this work. However, for getting better specificity and accuracy the following work developed CNN-BI-LSTM-GRU-AM technique for efficient breast cancer prediction.

5.3 Implementation of Hybrid CNN - BIL STM with Soft Attenuation Mechanism for efficient breast cancer prediction

This study proposes a hybrid CNN - BIL STM with Soft Attenuation Mechanism for efficient breast cancer prediction. Initially, the pre - processing is carried out based on Butter worth filter, which enhance the quality of image and to mitigate the noise from the input image. Following this, the cascaded Fuzzy C-means based segmentation process is made for dividing the space of image into different cluster regions with similar image's pixels values. The segmented image is fed to the feature extraction based on GLCM technique, which extract the most important features from the image and given to the classification stage. For classification, the hybrid CNN – BIL STM approach is used in this study that has advantage of both models, it helps to categorize and labelling the groups of pixels with higher prediction accuracy. Nevertheless, to improve the classification accuracy a novel CNN – Bi – LSTM – GRU - AM model is proposed in this research work.

5.4 Implementation of CNN-Bi-LSTM-GRU-AM topology for efficient breast cancer prediction

A novel feature extraction as well as classification techniques is developed in this research work for accurately diagnosing the breast cancer. The developed approach focuses primarily on enhancing the classification model to obtain more accuracy in predicting breast cancer. As a consequence, this work employs Deep CNN as well as VGG-16 for feature extraction, then the classification is carried out using a designed model that combines CNN, Bi-LSTM as well as GRU as well as an attention device to improve the classifier of prediction system. For training and evaluation purposes, the entire approach makes use of the MIAS and CBIS - DDSM datasets. Figure 1 illustrates the block diagram representation of the developed research work.

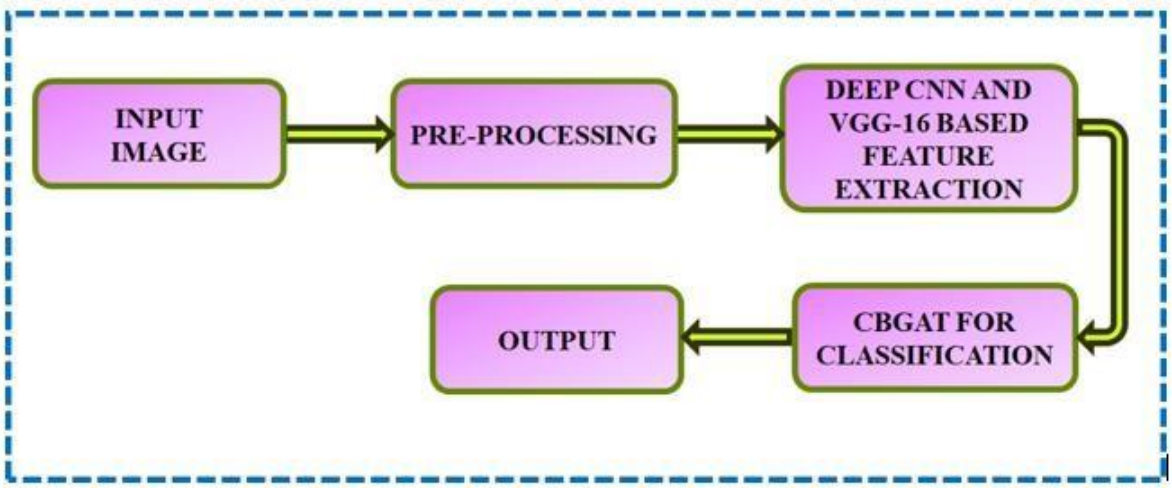

Figure 1 Block diagram of the proposed work

This study ensures that generalizability as well as strength of the developed systems are enhanced by combining various types of dataset. By incorporating the proposed model, better accuracy, sensitivity rate, F1 score as well as Specificity is attained. The modelling of this research work is described in below.

5.3.1 Pre-processing

It is the initial data processing phase that prepares data for more in - depth examination. It takes specific methods like The data will be scaled and resized during pre - processing and the data is normalized to a variety of variables or data attributes through this scaling procedure. Machine learning approaches require resizing since smaller images allow models to be trained more quickly.

5.3.2 Feature Extraction

Feature extraction is crucial for improving classification outcomes. For better classification outcomes, the developed system generates Deep CNN as well asVGG-16 model fused utilizing PCA for feature extraction technique. Deep CNN as well as VGG-16 are utilized individually to extract the features, which are then combined using PCA. To create a trained model set, the tracked data is divided into train as well as test halves. The trained portion is then given to developed classification technique termed CBGAT.

5.3.2.1 Deep CNN

The Deep CNN possess layers namely Input layer, convolutional layer, Max-Pooling layer, Model Training, Batch Normalization Layer, Dropout and Flatten layer, which are discussed below.

- **Input layer:** The specific features from pre-processed sensor data are listed as convolutional neural network's input vector.
- **Convolution layer:** The feature map that results from i_{th} convolution layer is as follows:

  $$x^{lj}{}_i = (b_j + \sum_{a=1}^{m} w^j{}_a x^{l-1j}{}_{i+a-1}) \quad (1)$$

  Where, j^{th} specifies the feature map, b_j indicates the Bias term, $m$denotes the kernel size, ath filter index, σspecifies activation-function,

- **Max - Pooling layer:** this layer determines the supreme value in each divider from the numerous dividers that emerge from output features of convolutional layers.
- **Model Training:** Final classification is carried out by the completely connected layers by combining the numerous learnt local structure elements from lower layer. An implemented method utilized a pair of max pooling layers, a convolution layer, flattened 2dimensional data into dimension data as well as fully connected layer to finish neural network.
- **Batch Normalization Layer:** Learning is more operative when batch normalization is employed it employed as regularization to avoid the model over fitting problem.
- **Dropout:** The regularization methods that avoid model over fitting problems involve dropouts. Tor and omly turn a certain percentage of the network's neurons, drop outs are inserted. Both the incoming and outgoing connections are turned off when the neurons are turned off. This is done to improve model learning.
- **Flatten layer:** For input in to the following layer, it transforms 2 dimensional array in to a 1 dimensional array. The size of the data is greatly decreased by flattening**.**

5.3.2.2 VGG-16

VGG-16 has been trained in the proposed method using Image net data with approximately 1000 classes as well as 1.2 million colour images. 16 convolutional layers using the activation function Re Lu and 3×3 kernel sizes makeup the original VGG – 16 model. Amax pooling layer with 2×2 kernel sizes is placed behind each convolutional layer to act as its shadow. The three fully linked layers are the final layers used as classifiers. The weight of the training result is stored in fully connected as well as convolutional layers, which controls a number of parameters.

5.3.2.3 Principal Component Analysis (PCA)

Deep CNN and VGG-16 are utilized for feature extraction as well as PCA is then used to combine these two models. Popular statistical technique PCA is frequently used to reduce the dataset's dimensionality. In all, 4224 features are extracted by concatenating the 128 features extracted by CNN, the 4096 features extracted by VGG-16 and the 128 features extracted by CNN. 100 features are then retrieved using the PCA employed.

5.3.3 Classification

As Convolution neural networks are widely used in engineering features, they are most applicable to LOS (Line of Sight). Similar to this, Bi-LSTM characteristics are typically used in time series analysis, which would increase the features dependent on time system. Furthermore, GRU is a version of LSTM and is progressive level of RNN (Recurrent Neural Network). Similar to merging earlier data series characteristics in time to the result, AM is significant. It is frequently used to get the result of prediction made using Bi-LSTM.

5.3.3.1 CNN (Convolution Neural Network)

It is a network type model as well as a subset of FFNN, which performs better in image processing. It works well for time series prediction Full connection layer, pooling as well as convolution layer are the three components that comprise CNN. The majority of convolution kernel is made out of each convolution layer. The convolution layer will be used to extract the data from the dataset.

Bi-LSTM and GRU: By incorporating the LSTM, a network model, long-standing issues such gradient explosion and the dis appearance of a gradient in RNN is resolved. A single repeating module with a straightforward internal structure is given in a typical RNN network. LSTM cell memory includes a number of models like forget, input as well as output gates. If Bi-LSTM model is produced by doing the LSTM module operation twice. The forget gate receives as input the most recent value of the momentum's output as well as the most recent value of its input. The mathematical procedure shown below in E results in the forget gate output value,

$$f_t=(Weight_f.[h_{t-1},x_t] + bias_f) \quad (2)$$

Where, the $bias_f$specifies the forget gate bias, $Weight_f$indicates the forget gate weight, $x_t$represents the provided value of present time.

Attention mechanism (AM): Attention mechanisms enable decoders to make use of the most relevant parts of input sequences by weighting combinations of whole input vectors with the high associated vectors given most weights. The crucial data is extracted from a large amount of data by manipulating the attention probability distribution, followed by the display of the important data and minimization of the traditional model. The central idea of AM is realized depend on activity of human consideration. Human vision has an ability to quickly arrive to the main location, after which it will immediately focus attention there in order to gather the necessary information in detail. Additionally, this method permits the value of information to be prioritized while excluding irrelevant information and selectively emphasizing the majority of the necessary information.

CNN-bi-LSTM-GRU-AM Training process: The following steps are used to describe the CBGAT model's training process.

- Input data: The proposed CBGAT training step receives the needed input data.
- Standardization of Input data: This strategy implemented the standardization system based on z-score for standardizing given data.
- Initialization of Network: Each layer of the developed model's biases and weights will be modified.
- Calculation of CNN layer: The input data is processed by this layer in order to extract the features.

- Estimation of Bi-LSTM layer: The subsequent value of the Bi-LSTM layer is ultimately derived when the consequent of the prior layer is assessed via a hidden layer of Bi-LSTM.
- Estimation of GRU layer: The output data from preceding layer Is examined by the GRU layer as well as outcome is derived from the GRU layer.
- AM layer estimation: This layer evaluates the output data from preceding layer to produce the desired outcome.
- Calculation of output layer: After comparing the output layer's calculated result with the group's provided data, the corresponding error is determined by calculation.
- Satisfaction level of prediction process: The training will end if any of the specified conditions for it, or it will continue if any of the prerequisites are not met.
- Error back propogation: The determined error is spread in the reverse direction, and the weight and bias of the layers will be adjusted.

Calculation phase of CBGAT model: The suggested model's prediction process is processed in the phases below:

- Input data: The prediction stage receives the necessary input data.
- Standardization of given data: The supplied information go through a correction process.
- Prediction: The developed trained model receives the standardized data as input to produce the related output value.
- Restoration of standardizing the data: The standardized value is an output value of developed model. This value will then be kept as the exclusive value.
- Outcome result: After the process of prediction is completed, the output will be obtained.

Adopting the two various data sets proficiently, the proposed model of CBGAT predicts breast cancer with better accuracy and within a short duration of time.

6. RESULTSANDDISCUSSION

In this research work, the CBGAT method is established for efficiently detect breast cancer prediction. The proficiency of developed system is determined by comparing it with other conventional techniques in terms of several performance indicators. In this study, Windows 10 OS is used for the test verification and comparison. Using the Anaconda Spider IDE, the developed CBGAT is run on Python 3.7.

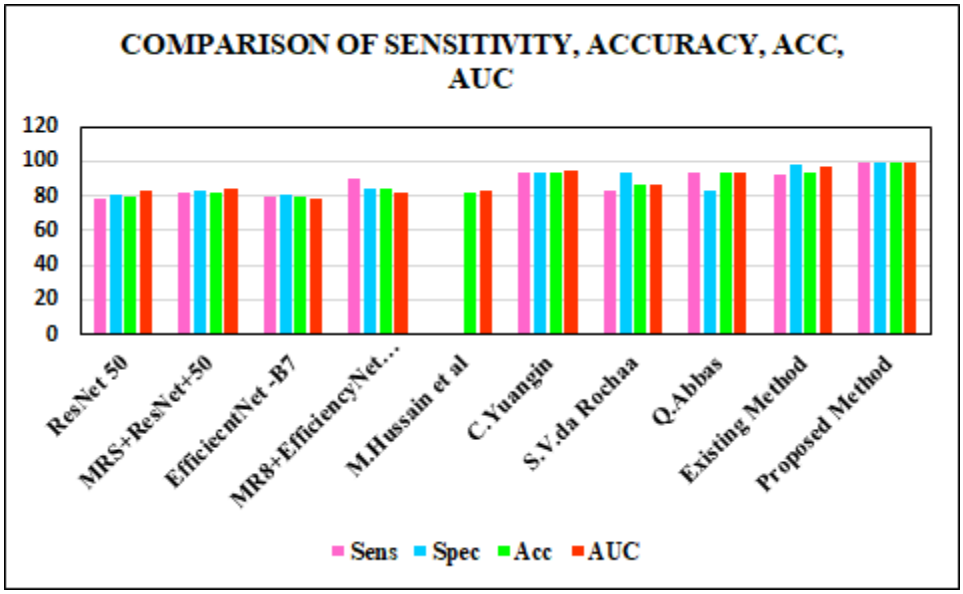

Figure2 Comparison of Sensitivity, Accuracy, ACC and AUC

The proficiency of the developed model overtakes other traditional approach. As represented in Figure 2, the implemented classification model attained highest sensitivity. Overall, the significance of developed model out performs other deep learning models using various dataset types. With the CBIS-DDMS dataset, the developed model demonstrated99.32% specificity, 99.08% sensitivity, 99.12% AUC as well as 98.65% accuracy. The proposed model's performance demonstrates both its superiority and resilience.

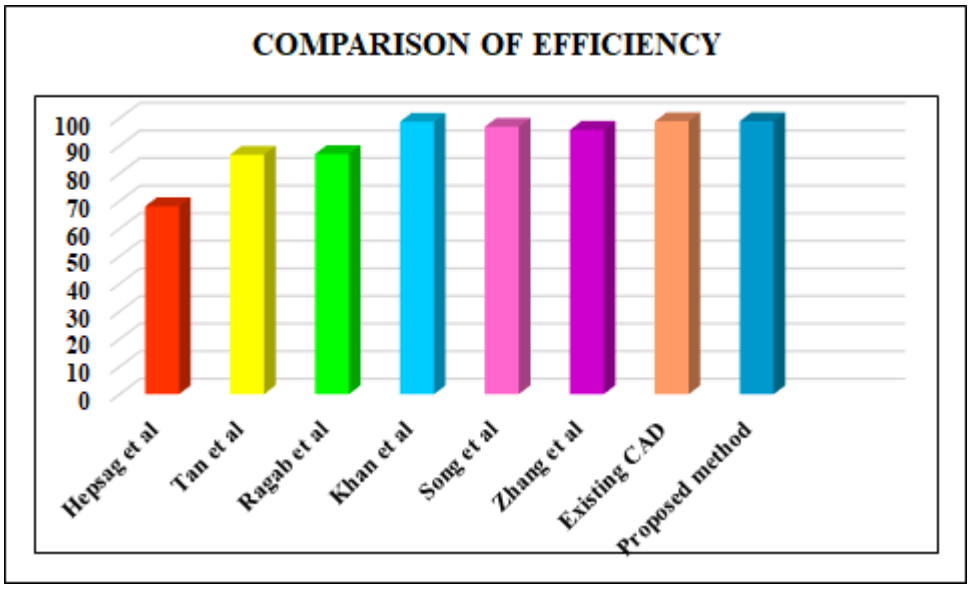

Figure 3 Comparison of Efficiency

Figure 3 illustrates the evaluation and comparison of developed CBGAT model with the relevant system to demonstrate the efficiency of developed model. Its how show effectively the developed model works with the two provided datasets. In terms of predicting breast cancer, the implemented classification model has better proficiency than other DL system. The developed model has the extreme classification accuracy for CBIS-DDSM as well as MIAS datasets with 98.65% and 98.89%, correspondingly, as illustrated in above figure.

Table1Comparison of proposed system for AUC and Accuracy

Techniques	Comparison of developed system For AUC and accuracy	
	AUC	Accuracy
MR8featuresonly	90.12%	80.00%
Deep CNN features only	93.45%	89.80%
FusingMR8andDeepCNN features	98.90%	97.99%
Proposed technique	99.12%	98.65%

The outcomes of classification are explored in Table 1 by comparing with the traditional methods. The AUC and accuracy rates of the developed method combines CNN-Bi-LSTM- GRU-AM, which achieved AUC at 99.12% and

Accuracy at 98.65%, respectively. The developed approach is higher than the existing method in terms of accuracy.

Table 2 Comparison of developed method with existing technique using MIAS dataset

Techniques	Comparison of developed system with conventional system Utilizing MIAS dataset			
	Res Net- Res Net	**Res Net-VGG**	**Existing**	**Proposed**
Sensitivity	0.87	0.85	0.97	0.99
Specificity	0.88	0.92	0.97	0.99
F1Score	0.91	0.93	0.98	0.98
Accuracy	0.92	0.94	0.95	0.98

Table 2 displays a comparison of conventional system using MIAS dataset with the proposed technique. With the MIAS dataset, the developed model demonstrated greater sensitivity, specificity, F1-score as well as accuracy values (0.99,0.99,0.98 and 0.98, correspondingly) than the other traditional approaches. Because of this, the suggested approach accurately predict breast cancer with some degree of proficiency.

7. THESIS ORGANIZATION

Chapter 1 Introduction: This chapter provides a general overview of detecting early breast cancer diagnosis. Moreover, various techniques and filters are also discussed in this chapter for precisely classify the occurrence of breast cancer.

Chapter 2 Literature Survey: The conventional systems uses Pre-processing, feature extraction and Classification techniques for an accurate diagnosis of breast cancer, which are discussed in this chapter along with their pros and cons.

Chapter 3 Breast cancer classification using Artificial Bee Colony optimized CNN: The use of artificial Bee Colony optimized CNN for breast cancer classification are discussed in this chapter. In addition, the outcomes attained by adopting the developed technique are also examined.

Chapter 4 Using Moth Flame Algorithm-Optimized CNN for enhancing Breast Cancer Detection in Mammogram Images: In this chapter, to enhance the breast cancer detection in mammogram images, Moth flame Optimized CNN are discussed and the results obtained by using the implemented techniques are also discussed.

Chapter 5 A Deep Learning Approach for efficient breast cancer diagnos is using hybrid CNN- BIL STM with soft attention mechanism: In this chapter, presents a sophisticated diagnostic framework integrating pre-processing, segmentation, feature extraction and hybrid CNN-BIL STM with attention mechanism, showcasing superior performance in breast cancer detection over traditional methods.

Chapter 6 Efficient Breast cancer prediction using CNN – Bi - LSTM-GRU - AM: This chapter deals with the use of CNN – Bi – LSTM – GRU –AM method for efficient breast cancer classification. Furthermore, the obtained outcome from the developed model are also discussed.

Chapter 7 Results and discussion: In this chapter, the outcomes from the developed research work is discussed and to fore show the proficiency of the proposed work, comparative analysis is carried out with existing approaches.

Chapter 8 Conclusion and future scope: The conclusion of entire research work is discussed in this chapter and the recommendations for the future work are also examined.

8. CONCLUSION

The possibility of breast cancer is efficiently predicted in this research work by adopting the DL techniques. This work offered a novel feature selection and classification method to accurately predict breast cancer. For feature extraction, this work developed VGG-16 as well as Deep CNN. PCA is used to combine the retrieved characteristics from these two models. The train and test segments are produced using the extracted features. The prediction process will be used to the testing data and trained model to identify breast cancer. On several datasets, the suggested technique's robustness is evaluated. Ideal results were achieved with 98.65% accuracy for CBIS-DDSM dataset as well as 98.89% for the MIAS dataset using two different datasets. For evaluating the effectiveness of the developed

model, a number of performance metrics like accuracy, sensitivity, specificity, F1-measure as well as AUC are employed. The analytical outcome exhibited that the developed model has superior proficiency than the traditional techniques. As a result, this study aid medical professionals for making an accurate diagnosis of breast cancer and treating patients accordingly.

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